DEEP LEARNING APPROACHES FOR MULTI-CLASS DISEASE DETECTION AND CLASSIFICATION IN RETINAL IMAGES

Dr. Mahesh Kaluti[1], Aishwarya M. Y.[2], Punya R.[3], Sathvik C. N.[4], Chandan K. R.[5]

[1,2,3,4,5] Department of IS&E, PES College of Engineering, Mandya,India

ABSTRACT

Many techniques are designed to increase accuracy diagnoses of diseases in retinal images such as hypertensive retinopathy. Convolutional neural networks (CNN) have been employed in various techniques to segment blood vessels in retinal images. These techniques sometimes fail to effectively segment the blood vessels of retina of eye and produce extra noise and we have with this drawback, we present a technique to detect blood vessels in retina of eye images using thousands of blocks (patches) from each of the image. This technique is on a CNN where it contains four convolutional layers followed by relu, max pooling four layers, two layers are fully connected and one layer is the softmax for segmenting blood vessels.

KEYWORDS: CNN, CLAHE, Gaussian Filter, Hypertensive Retinopathy

INTRODUCTION

Many eye pathologies are related to the retina, such as (hypertensive retinopathy and glaucoma), which are the most frequent and deadliest disease that affects 9.4 million people every year is anticipated to rise [1]. A retinal image is used to acquire the fundus camera to see through a pupil of eye the rear inner surface of the eyeball known as the retina. It generally contains the optic disc, optic cup, blood vessels, fovea and the retinal background. The application of digital imaging helps the ophthalmologist process system retinal images to help in clinical diagnosis and treatment. similarly, retinal image evaluation notably improves the diagnostic cost of those images.

An identification and diagnosis of this hypertensive retinopathy which will requires the segmentation of objects which are normal present inside the retina of eye shown as blood vessels is shown in figure 1. Segmentation of blood vessels is considered the core for diagnosing eye diseases such as hypertensive retinopathy. The ophthalmologist can use the blood vessels structure to detect and classify a variety of retinal pathologies, as well as diseases of the brain and heart, both are linked to the variations which aew not normal in blood vessels. So, changes in the morphology of the retina arterioles and venules has a significant diagnostic value present. The purpose of blood vessels detection is to distinguish between the various blood vessels structure tissues, as it will either be wide or narrow from retinal image background and other normal objects in retina of eye image including the optic disc, macula and abnormal objects.

Because of the non-invasive fundus imaging and critical information in blood vessels, which is important for detecting and diagnosing a range of

retinal diseases. However, blood vessel detection studies have a lot of attention in recent years.

Blood vessel segmentation is separated into three approaches: rule-based, machine-learning approaches and deep learning approaches. Thresholding,tracking vessel, matched filtering, multi-scale procedures, mathematical morphologies, and model is based processes are examples of rule-based approach. Classification and clustering are examples of the machine-learning approach. CNN is an example of a deep learning approach.

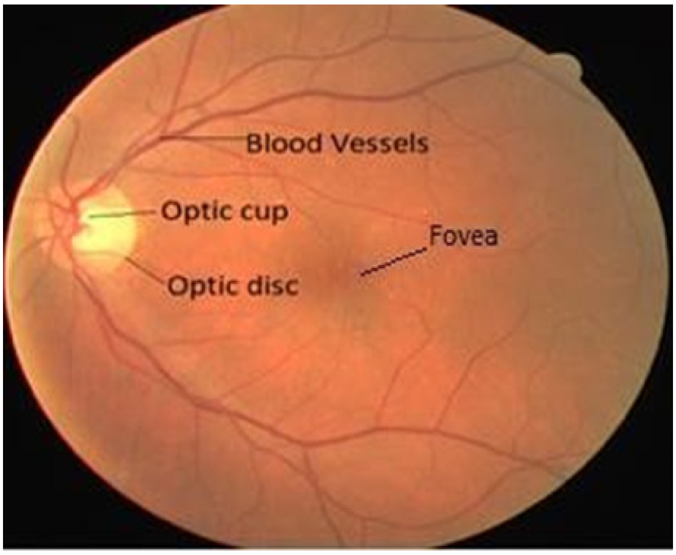


Fig.1: Normal retina objects

CNNs have been employed in a variety of techniques to segmentation of blood vessels in images of retina, the convolutional filters constrained receptive fields is challenging. Further, these algorithms frequently fail to segmentation of retina's blood vessels effectively and produce extra noise. in this paper, extracted thousands of blocks (patches) from each image, followed by applying rotating and flipping to these

patches to increase the training dataset, then applied CLAHE technique to increase the low contrast in these patches and Gaussian filter to remove the noises. Finally, the proposed system is based on a CNN that contains four convolutional layers followed by relu, max- pooling four layers, layers which are two and fully connected and one layer called softmax for segmenting the blood vessels.

The paper is structured as follows: Section II will explicitly discuss all related work.Section III describes the datasets. Section IV explains the pre-processing procedure. The paper presents the methodology and a CNN model in Section V, followed by experiments and results in Section VI, and a conclusion in Section VII.

2. WORK RELATED

Various approaches have been used to identify blood vessels in retinal images. SegLazar and Hajdu [2] used directional height statistics to segment blood vessels in retinal images ment blood vessels in retinal images, Lazar and Hajdu

[2] An approach called "used directional height statistics" is used to segment retinal veins. This method creates a peak on the intensity profile that resembles a Gaussian distribution when a direction is perpendicular to the vessel's length. To differentiate between vessels and non-vessels, a scoring guide based on the standard deviation is used. Chang et al. [3] have demonstrated the effectiveness of this approach in segmenting retinal veins. This method uses a line and edge detector for retinal blood vessel segmentation, followed by the application of the Canny edge locator to generate an edge outline from the enhanced image.. The goal of this strategy is to remove the problem of misclassification. Soares et al. [4] used a 2-D Gabor wavelet and supervised classification has been used to detect blood vessels in fundus images. Each pixel is classified as a vessel or not using a Bayesian classifier, based on its feature vector composed of pixel intensity and Gabor wavelet transform responses collected at various scales. Based on mathematical morphology and K-means clustering. Gehad Hassan et al.[5] suggested a technique for segmenting blood arteries. The image is smoothed using mathematical morphology to enhance blood vessels. After being enhanced, the image undergoes segmentation using the K-means clustering algorithm.method. Kumar et al.[6] described a method for identifying retinal vascular structure using two-dimensional matching filters with Laplacian of Gaussian (LoG) kernel functions are applied to fundus retinal images. Then, Contrast Limited Adaptive Histogram Equalization (CLAHE) is performed.approach was used to enhance the retinal vascular. Zhang et al [7] created a novel segmentation approach for detecting blood vessels in retinal images based on snake shapes. The proposed method is separated into three stages using a Hessian feature boundary-based technique, the retinal image was segmented into areas based on the extracted linear structures.

Each region was represented by an image using the average impact of pixel intensities. The snake contour function was then applied to estimate the boundaries of the image near vessel edges were to actual ones. Finally, the final vessel region was obtained using a region-growing process. The researchers devised a reliable method for segmenting retinal blood vessels [8]. This strategy consists of two main points: Each segmented candidate region is analyzed for featuresA support vector machine (SVM) is utilized to classify regions of interest for classification. The proposed method's performance was assessed using three databases: DRIVE, STARE, and AFIO (Armed Forces Institute of Ophthalmology).

[9] Orlando et al. described a supervised learning system for retinal blood vessels based on structural support vector machines. The suggested approach was constructed on the foundation of a completely A strategy called connected conditional random field (FC-CRF) was used to evaluate the STARE public datasets. CHASEDB1, and DRIVE using both quantitative and qualitative approaches. Sensitivity, F1-score coefficients, and G-mean were used to evaluate performance [10] Jin et al. suggested a CNN-based deformable U-Net (DUNet) model for blood vessel segmentation that uses retinal blood vessels local properties by merging high and low-level features. In DUNet, sampling up operators are used to increase output resolution, capture contextual information, and enable specific localisation. Several image preprocessing procedures will be used to improve the vessel's features.

3. DATASETS

Different datasets are used for detection of normal and objects in retinal images such as blood vessels have been described as follows.

A. STARE

There are 397 retinal images in this dataset [18]. The dataset consists of 700x605 pixel images with 24 bits per pixel. The dataset aims to facilitate the detection of optic disc and blood vessels. The dataset comprises 700x605 pixel images, with each image having 24 bits per pixel. Its main objective is to enable the detection of optic disc and blood vessels with utmost accuracy.and each image inside it is identified as related to one or more of thirteen different diseases that are used for classification.

B. DRIVE

This dataset consists of 40 retinal images obtained from the Dutch diabetic retinopathy screening program. The patients aged 25-90 years old, with 33 images having no signs of DR and 7 exhibiting mild symptoms. The dataset is divided into a training and test set, each with an equal number of images

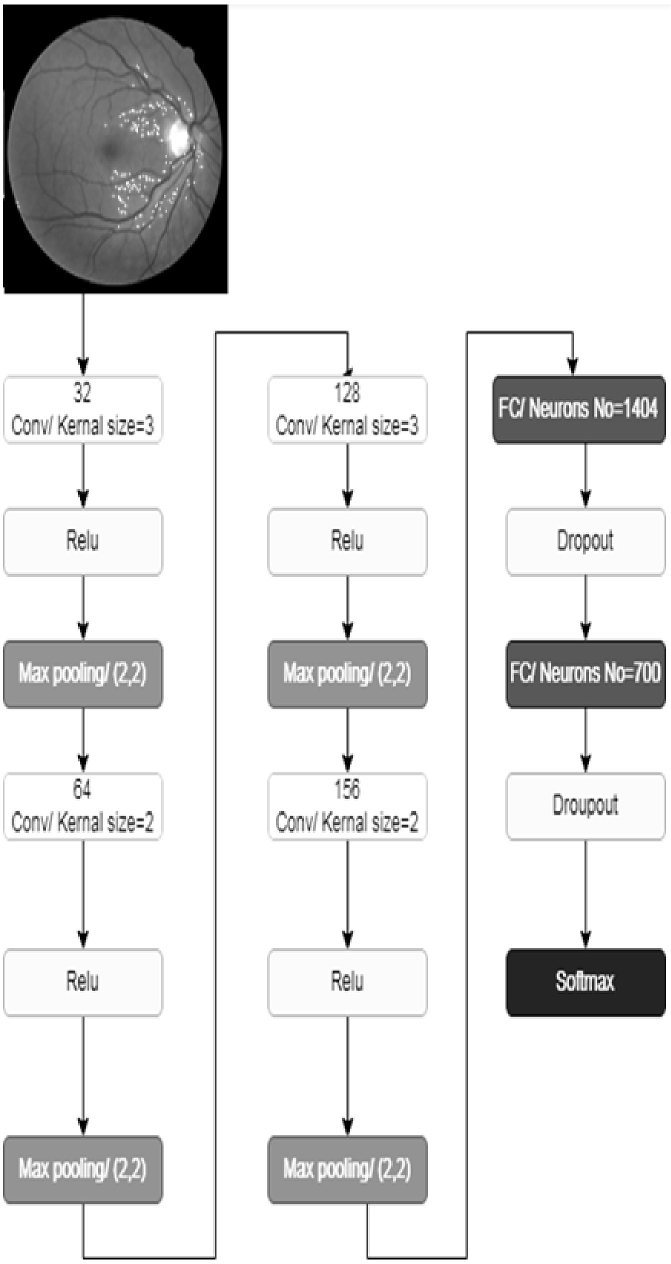


Fig.2: The proposed CNN architecture model

4. PREPROCESSING

Image preprocessing is necessary for enhancing the quality of retinal images, as low-quality images might reduce network performance and it is extremely important to ensure that all images are homogeneous and that the features of the images are improved. The following steps are used for the preprocessing.

1. Image Converting: we converted the retinal image to a gray channel because it carries the most contrast for the network of the vessels.
2. Image Patches extracting: patches with dimensions 48*48*1 from each gray channel image are extracted.
3. Image Enhancing: CLAHE is an effective technique for improving the poor contrast of medical images and enhancing the contrast of fundus images. The CLAHE approach produces some noise in the images that is eliminated using the Gaussian filter.

5. PROPOSED METHOD

CNN is a version of the Multilayer Neural Network model designed to analyze two-dimensional input which considers being one of the Deep Learning architectural models.

The proposed CNN contains four convolutional layers followed by Relu There are four convolutional layers followed by four max-pooling layers, two fully connected layers, and a softmax layer for classification. We have used data augmenting to increase the training dataset and improve the adaptability and performance of the CNN. From each image, 2200 patches with a size of 48*48*1 are extracted, and each extracted patch image is rotated flipped. The total number of patches used for training on DRIVE dataset is about 160000 patches and 665000 patches on STARE dataset. The proposed model architecture is shown in Fig. 2.

6. EXPERIMENTS AND RESULTS

System was built using Python & Keras on Tensor Flow framework, evaluated on NVIDIA Tesla K20 GPU with 8 GB RAM. Hyper-parameters are variables pre-selected or optimized through random search, grid search, and gradient-based methods in deep learning networks.. However, the speed of the process of tuning hyper-parameters is achieved by manual hyper-parameter tuning as shown in table 1. In order to achieve accurate and successful image detection, it is necessary to update the model parameters. This is accomplished by utilizing the Stochastic Gradient Descent (SGD) algorithm to minimize the cross entropy loss. Through this process, the model is able to learn and improve its ability to accurately identify images.

Parameters	Values
Optimiser	SGD
Learning Rate	0.01
Mode	triangular
Dropout	0.5
Epochs	40

Table 1: The hyper-parameters of proposed method.

A. Results and Discussion

We are pleased to showcase the exceptional performance of our suggested technique on two datasets. Our CNN-based method was rigorously compared to other available retinal vessel-based segmentation methods, and we are confident in the results presented in Table 2. Our meticulous analysis yielded impressive accuracy scores of 0.962 on the DRIVE dataset and 0.972 on the STARE dataset, coupled with remarkable sensitivity scores of 0.782 on DRIVE and 0.811 on STARE.

a) Preprocessed Images of the DRIVE dataset

b) Extraction of blood vessels.

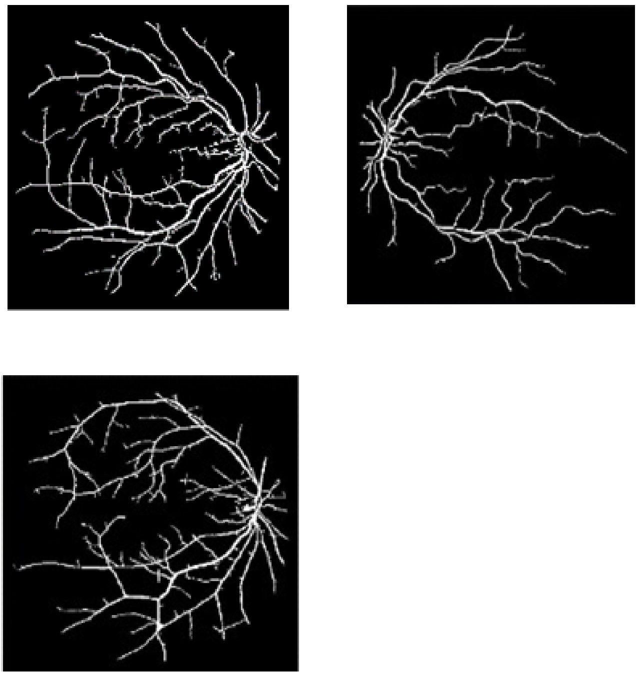
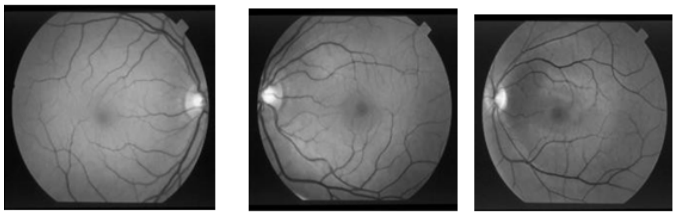
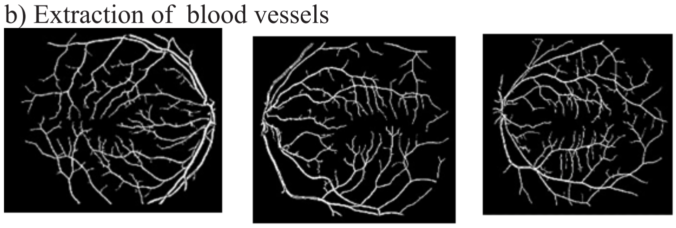


Fig 3: The proposed model results.

a) Preprocessed Images of the STARE dataset.



b) Extraction of blood vessels



Dataset	*Se*	*Sp*	*Acc*
DRIVE	0.782	0.976	0.962
STARE	0.811	0.973	0.972

Table 2. : Performance evaluated of method proposed on the two datasets mentioned

The proposed system describes how a new method outperforms existing techniques in terms of its effectiveness on two different datasets. The new method achieved higher accuracy.

The model was tested on the DRIVE dataset, as presented in Table 3.. The method showed better sensitivity on the STARE dataset compared to others as shown in table IV.

The new method proves to be more accurate and more sensitive in recognizing what it needs to, according to specific tests conducted using these two datasets.

Type	*Method*	*Se*	*Sp*	*Acc*
Machine Learning	Geetha Ramani et al [20]	70.79	-	95.36
	Hassan et al [5]	-	-	95.10
	Singh et al [21]	67.35	-	94.59
	Franklin et al [22]	68.67	-	95.03
Deep Learning	Yang et al [11]	0.797		0.951
	Yan et al [17]	0.773	0.982	0.953
	Jin et al [10]	0.796	0.98	0.956
	Wu et al [23]	0.799	0.981	0.958
	Proposed Method	**0.782**	**0.976**	**0.962**

Table 3: "A comparative analysis of performance to different methods on dataset DRIVE"

Type	*Method*	*Se*	*Sp*	*Acc*
Machine Learning	Hoover et al [24]	67.51	95.67	92.75
	Staal et al [19]	69.70	-	95.16
	Jiang et al [25]	-	-	90.09
	Chakraborti et al [26]	67.86	95.86	93.79
Deep Learning	Jin et al [10]	0.760	0.986	0.963
	Wu et al [23]	0.796	0.986	0.967
	Tamim et al [27]	0.780	0.982	0.963
	H. Boudegga [28]	0.806	0.992	0.981
	Proposed Method	**0.811**	**0.973**	**0.972**

Table 4: : "A comparative analysis of performance to different methods on dataset STARE"

7. CONCLUSION

The CNN-based segmentation of retinal blood vessels is an effective method which has attracted the attention of numerous researchers during the past five years. There are instances when these algorithms are unable to correctly segment the blood vessels of retina. In order to expand the training dataset, we extracted thousands of patches from each image in this article and then rotated and flipped them. For improving contrast of these patches and get rid of the noise, we used a Gaussian filter and CLAHE during the preprocessing stage. Lastly, we segmented the blood vessels using the CNN. We have attained a respectable sensitivity of 0.962, 0.972 on DRIVE and STARE, respectively, and an correctness of 0.782, 0.811 on DRIVE. Additionally, the benchmark and the suggested method are contrasted.

REFERENCES

1. Publication by the American Heart Association titled "Executive Summary: Heart Disease and Stroke Statistics-2016 Update". The publication was co-authored by D. Mozaffarian, Benjamin EJ, Go AS, Arnett DK, Blaha MJ, Cushman M, Das SR, de Ferranti S, Després JP, Fullerton HJ, Howard VJ, Huffman MD, Isasi CR, Woo D, Yeh RW, and was released in 2016.; Circulation 133(4): 447–454.
2. The paper "Segmentation of vessels in retinal images based on directional height statistics" by Lazar, I., and Hajdu, A. was published in the IEEE Engineering in Medicine and Biology Society's 2012 Annual International Conference (pp. 1458–1461).
3. A 2009 conference on multimedia signal processing and intelligent information hiding presented paper a new way to segment retinal blood vessels. The method used a line operator and edge detector. The paper's authors are Chang, C. C., Lin, C. C., Pai, P. Y., and Chen, Y. C.
4. "Retinal vessel segmentation using 2-D Gabor wavelet and supervised classification" by Soares et al. in IEEE Transactions on Medical Imaging, 2006, vol. 25, no. 9, pp. 1214-1222.
5. Hassan, Gehad, Vaclav Snasel, Nashwa El-Bendary, Aboul Ella Hassanien, and Ali Fahmy. "Retinal blood vessel segmentation approach based on mathematical morphology." Procedia Computer Science, vol. 65, 2015, pp. 612-622.
6. Kumar, D., Pramanik, A., Kar, S. S., & Maity, S. P. "Retinal blood vessel segmentation using matched filter and Laplacian of Gaussian." Signal Processing and Communications International Conference (SPCOM) 2016, IEEE, pp. 1-5.
7. Zhang, J., Tang, Z., Gui, W., & Liu, J. "Retinal vessel image segmentation based on correlational open active contours model." Chinese Automation Congress (CAC) 2015.
8. Awan, A. W., Awan, Z. W., and Akram, M. U. "A robust algorithm for segmentation of blood vessels in the presence of lesions in retinal fundus images." Imaging Systems and Techniques (IST), 2015 IEEE International Conference on, pp. 1-6.
9. Orlando, J. I. and Blaschko, M. "Learning fully-connected crfs for blood vessel segmentation in retinal images." Medical Image Computing and Computer-Assisted Intervention, Springer, 2014, pp. 634-641.
10. "Dunet: A deformable network for retinal vessel segmentation," by Jin et al. (2019) presents Dunet, a new approach to retinal vessel segmentation that is outperforms state-of-art methods on public datasets.